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Spatial Patterns and Multi-Dimensional Impact Analysis of Urban Street Quality Perception under Multi-Source Data: A Case Study of Wuchang District in Wuhan, China

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Abstract: The human spatial perception of urban streets has a high complexity and traditional research methods often focus on access surveys of human perception. Urban streets serve as both a direct conduit for pedestrians' impressions of a city and a reflection of the spatial quality of that city. Street-view images can provide a large amount of primary data for the image semantic segmentation technique. Deep learning techniques were used in this study to collect the boring, beautiful, depressing, lively, safe, and wealthy perception scores of street spaces based on these images. Then, the spatial pattern of urban street-space quality perception was analyzed by global Moran's *I* and GIS hotspot analyses. The findings demonstrate that various urban facilities affect street quality perception in different ways and that the strength of an influencing factor's influence varies depending on its geographical location. The results of the influencing factors reveal the difference in the degree of influence of positive and negative influencing factors on various perceptions of the visual dimension of pedestrians. The primary contribution of this study is that it reduces the potential bias of a single data source by using multi-dimensional impact analysis to explain the relationship between urban street perception and urban facilities and visual elements. The study's findings offer direction for high-quality urban development as well as advice for urban planning and enhanced design.

Keywords: urban quality; human perception; spatial regression; geospatial big data; urban computing

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1. Introduction

With the increasing rates of urbanization, urban construction, and population density growth, the global development of high-quality cities is imminent. The street constitutes a direct display of urban imagery, serving as the principal site of citizens' activities, and has a significant impact on the quality of life of urban residents. At present, big data technology has been deeply integrated into the urban digital transformation [1–4]. The deep integration of urban digital transformation and big data technology provides a foundation for the scale, refinement, and intelligence of urban spatial research. For planning and architectural research, the combination of streetscape imagery and geographic information breaks through the limitations of traditional field collection methods. It also has a positive effect on large-scale urban measurement research. At present, street-view imagery has high coverage in large cities around the world and provides high-density and massive images based on urban road networks [5]. Street-view images have been employed in the study of the spatiotemporal traffic mode [6], the spatial perception score [7], the evaluation of urban greening [8], and the earthquake risk assessment of cities [9]. Street-view photographs have also opened up new possibilities for the study of urban space; however, there remains a need to investigate the different ways of combining street-view images to conduct research on the effects of urban street-space quality.

Different cities have different urban characteristics, and there is variation within different blocks and different spaces of the same city [10]. These factors lead to local differences in street-space perception in an urban area. Therefore, the study of spatial perception not only has global characteristics but can also capture the distinctive characteristics of blocks within a city. Many Western countries emphasize the protection of urban characteristics and plan regional development via urban planning documents (e.g., the Vancouver City Plan, the Sheffield Development Framework, the London Plan 2021, etc.). Similarly, some studies in China have focused on providing different guidance in different zoning control zones. An example can be found in the work of scholar Yu, Z. Taking Harbin as an example, the author selected 10 places with different period characteristics in order to discuss the protection and regeneration of urban characteristics under the Chinese planning system [11]. The case in this study, similar to that of Harbin, describes a large provincial capital city in central China. Possessing the comprehensive characteristics of a modern city, historical city, comprehensive city, and representative city, the Wuchang District is one of the central urban areas of Wuhan city. Its urban street characteristics cover many periods, and some streets retain the historical characteristics of different periods. This is one of the core reasons for performing this study using the Wuchang District of Wuhan.

The principal objective of this study is to answer the following questions:

What are the characteristics of urban street spatial perception scoring in spatial patterns in relation to the scoring situation based on street-view images? Is the quality score, which leads to such local differences, related to the spatial measures of urban public facilities and the human visual scale? If they are related, how do different facilities and different spatial visual measures affect the perception of street spatial quality?

The main contribution of this study lies in constructing a research framework for the assessment of the multi-dimensional impact of urban street spatial perception based on multi-source data. These dimensions include the autocorrelation of the overall spatial pattern, the influence of the public facility distribution, and the influence of the human visual scale quantification index. This paper transforms perceived subjective problems into objective data problems, undertaking a large-scale investigation of the measures and factors capable of influencing spatial perception scoring. Past research usually used single-source data to conduct urban spatial studies of perceived impact mechanisms. However, the multi-source data used in this study provides multiple perspectives. As the dependent variable, the spatial measure index of the human visual scale compensates for the limitations of urban public facilities as independent variables, reducing the potential bias of using a single data source. At the same time, the conclusions from this research can provide basic indicators and references for high-quality urban development, as well as a people-oriented quantitative perspective for future urban quality improvement strategies.

2. Literature Review

2.1. Perceived Spatial Quality of Urban Streets

Street space consists of streets and the various elements along them. The capacity of street space is the ability of the street to sustain a particular scale of people passing, staying, and performing other activities, which is the premise and foundation of all action [12]. Early studies on urban street space were mainly based on urban macro theory. *The Image of the City* categorized urban spatial elements into five categories: roads, boundaries, zones, nodes, and markers [13]. In the early days, the study of urban streets was closely related to urban roads, and these features were considered to be part of the community [14]. Gehl, J., proposed that streets and squares are the main factors in city composition and that other facility functions are arranged around them [15]. In terms of discussing urban streets and their related elements, Cullen, G. mentioned that the active factors of the street landscape can increase the appeal of street space [16]. At the same time, the sense of spatial enclosure is also closely related to the oppressive perception of pedestrians in the street [17]. In the field of urban morphology, streets constitute important public spaces. In the relevant description of the term street (cadastral) model, the space between blocks is the public space network, while the urban street network model uses different categories. For example, rule grids composed of geometric laws are generally planned. With the organic development of urban roads, the organic or deformed grid becomes another form of street grid.

Perception is the result of human process filtering, which is due to the environment inspiring emotions and providing people with more information than human processing power can handle at once [18]. Whether the city streets are interesting or not can reflect whether the city is interesting or not. Therefore, the quality perception evaluation of streets can reflect the influence of the environment on people and can also be used to understand the spatial quality of a city. In the macro dimension of urban activities, street spatial perception research based on GIS, which utilizes road network data, POI data, etc., is more commonly used as the basis of perception research [19]. Some scholars have also constructed a street walkability measurement model including feasibility, accessibility, safety, comfort, and pleasure by combining street view maps and Arc GIS [20]. On the pedestrian scale, some scholars have calculated urban spatial measurement indicators such as the street aspect ratio, green viewing index, and sky visual factor, and then explored their relationship with spatial perception [21–24]. The most direct manifestation of pedestrians' perception of street space comes from their vision. Visual appropriateness is important for the places most likely to be visited by people from wider and various backgrounds [25], and, obviously, urban street spaces are such places.

Moughtin, C. pointed out that, besides being a natural element of the city [26], streets are also a social factor, inseparable from the social, economic, cultural, and historical background. It is noteworthy that research on street perception varies depending on the cultural context. Western and Eastern nations have differing starting conceptions of urban planning, which affects the layout of urban streets and how people perceive space. Due to varying environmental experiences and personal evaluation standards, it is conceivable that different social groups will have diverse opinions about the same location. In the West, street space is an important space for communication and gathering. On the contrary, in Chinese history, under the long-term influence of the ritual system, people possess a strong sense of the boundary between the inner and outer urban spaces. As a result, street space was not valued for a long historical period, unlike Western street space which has diversified functionality and high vitality. However, with the evolution of urban development and new social thought, the function of street space in China has grown more complex, and its quality has continued to improve. Still, we cannot ignore differences in social backgrounds. Therefore, the discussion of street perception and its influencing elements mainly relates to the Chinese context. In order to better realize the specific context, this study first used the pre-training model of China to score the street view of the research area. Later, the influence mechanism was analyzed based on the urban cultural background and specific street characteristics in order to achieve more targeted analytical conclusions.

2.2. Application of Big Data Tools in Urban Spatial Research

The complexity of urban space makes the direction and dimensions of urban research more diverse, and the amount of data available on various attributes of cities is relatively large. Traditional urban planning data primarily comes from spatial geographic information and urban planning management systems, which sometimes have lagging and regional restrictions. Supported by computer technology, big data approaches make up for the needs of primary urban data in terms of data volume and accuracy. Currently, the most widely used data sources for urban spatial street research mainly include street-view maps [27], urban facility POI [28], and cell phone big data [29]. Street View Map is an Internet-based live-view electronic map service that provides a new type of map experience centered around the human perspective [30]. The most commonly used street-view imagery processing technology is image segmentation based on deep learning, and image segmentation contains various types of technologies such as panoramic segmentation [31], semantic segmentation [32], instance segmentation [33], and so on. Among them, semantic segmentation technology is widely used, being among the principal technical methods utilized in this paper. Semantic segmentation is processed by classifiers based on specific theories to categorize the pixel points in the image. This method is then combined with image feature extraction techniques to obtain the segmentation results.

The semantic segmentation of images based on convolutional neural networks is a leap forward from traditional semantic segmentation. Nagata S. et al. used semantic segmentation and statistical modeling of Google Street View images to assess streetscape walkability. The results of the study found that the walking vigor of older women has a higher correlation with streetscape walkability than older men [34]. Xia et al. used image segmentation techniques to generate a street-level SVFf map to assess the urban thermal environment and propose more targeted urban planning measures [35]. Many studies have confirmed the higher feasibility of street-level images in urban spatial research. Urban POI data, which is mainly acquired through the map API interface, the urban big data open platform, and field research data integration, is the most commonly used data source for urban spatial research. POI is an important data source for spatio-temporal big data in the fields of urban spatial structure [36], human activities [37], and ecological development [38], and also has a significant reference value for urban spatial planning and infrastructure service construction. Mobile big data has considerable advantages in studying crowd mobility and social patterns. For example, Fina S et al. compared travel patterns in selected monocentric and polycentric urban areas in Germany using mobile big data to test hypotheses of transit-oriented regional development and congestion risk in transport networks [39]. Many studies have combined the above research methods to achieve more comprehensive data coverage, and this study aims to assist in understanding spatial and temporal mobility patterns in different city types.

2.3. Trends in Urban Street Perception Research and the Innovativeness of This Study

Over the preceding decades, research on urban perception has been continuously updated. The application of multi-source big data has brought new opportunities for research on urban perception [40]. Many studies have quantitatively evaluated the spatial perception of streets through indicators such as human activity patterns, built environment measures, and field visit results. Pedestrian counts and qualitative street studies have been used to explore the cultural differences and similarities in street vitality perceptions between street users in the United States and Turkey and to analyze the physical factors that contribute to increased street vitality [41]. Field visit results often need to rely on more extensive sample data. For example, Zheng et al. investigated the preferences and perceptions of street trees among 884 city residents in a metropolitan area in South Korea to explore strategies for improving the spatial quality of urban streets [42]. Meanwhile, advances in urban analysis tools provide new methods to describe, quantify, and present street quality perceptions. For example, Lu et al. used a regression model to quantify the correlation between vitality and the factors affecting the built environment in two cities [43]. LIU et al. used machine learning semantic segmentation, GIS, and semantic differential (SD) to obtain spatial data and perceptual evaluations of Qingdao coastal streets. They constructed a regression model with imageability, closure, human scale, transparency, and complexity as dependent variables [44].

A wide array of complex factors influence urban spatial perception. For example, Jiwei Xu et al. used random forest regression to reveal the non-linear effects of street canyon properties on human perception [45]. This research was principally conducted from the perspective of street-space characteristics. Additionally, a number of scholars have paid attention to the correlation between urban spatial perception and urban vitality [46]. Urban perception is also highly correlated with environmental exposures and urbanization factors. It was found that population density, impervious surface area, major roads, traffic air pollution, tree coverage, and NDVI resulted in statistically significant differences in levels of safety, liveliness, and perceived location beauty [47]. The study was exclusively focused on capturing the relationship between the factors associated with built-environment exposure and partial positive perception. Indeed, due to the complexity of factors influencing how an urban space is perceived, it is difficult to find all the influencing factors in a single study. For example, Fan Zhang et al. investigated how the resulting objects—trees, grass, roads, bridges, houses, etc.—contribute to the curation of a certain experience [48]. Thus, we developed a comprehensive research paradigm to assess the impact of urban perception based on previous studies. In contrast to previous research, this study considers the macro and micro influences of the urban micro-level on the layout of various functional facilities.

To summarize, existing research on big data technologies in urban street space has shown an upward trend. The development and application of semantic segmentation technology encouraged the algorithm's ongoing improvement, and its potent capability for image processing provided a strong framework for the execution of large-scale image data studies. The granular coverage of POI data in cities also provided a source of data for this study. Urban streetscape data sources, POI big data, and related technologies are all combined in this study. However, most of the existing studies still have some limitations. First, although some studies have focused on the relationship between urban perception and multiple elements, the level of discussion is relatively homogenous, and due to the complexity of urban elements, fewer studies have focused on multi-dimensional exploration at different scales. Secondly, we also found that although many studies have conducted regression analysis on city perception and city-influencing elements, they mainly focus on the global area and pay insufficient attention to the local differences in the degree of influence in different geographical locations. This paper refined the number of local differences in influencing factors through semantic segmentation technology and geographically weighted regression analysis. The geographically weighted regression analysis approach was chosen as the calculation method for the level of contribution of influencing variables in public facilities because it can recognize the difference in local contribution level. A quantitative approach for spatial indicators on the human visual scale was suggested in order to implement the regression model development, based on the available research. Taking the Wuchang District of Wuhan as an example, this study provides new ideas in both a theoretical framework and technical methods, intending to guide the sustainable development of urban street quality and the optimization of street spatial perception.

3. Data and Methodology

3.1. Research Framework

The main framework of the research methodology of this study is as follows:

In the first stage, it was necessary to obtain street image data using geographic information. We first collected the road network data in Wuchang District, Wuhan, through Open Street Map (OSM), the tool used in this study. Such data include urban expressways, main roads, secondary roads, and other side roads. For this study, 26,000 sampling points were generated. The Baidu Street View API was parsed and used to obtain the street-view images. Then, it was necessary to obtain Baidu maps of Wuchang District public facility interest points to provide essential data support for the correlation study.

In the second stage, based on the urban six perception pre-training deep learning model of the China University of Geosciences (Wuhan) [49], we scored all street-view images using six categories: boring, beautiful, depressing, lively, safe, and wealthy. They were visualized in Arc GIS according to the coordinates of street-view acquisition points. The spatial distribution pattern of spatial autocorrelation and the scoring of different streetscape images were also investigated via the study of the spatial quality of urban streets at the macro level, i.e., from a global perspective. This part mainly quantified the spatial characteristics of different dimensions of the global Moran's I index and hot-spot analysis. The aggregate distribution of categories yielding high and low perceptual scores was then discovered. This can help researchers analyze the spatial quality pattern of urban streets more clearly, realize a comprehensive study at the global level, and provide measurement support for the future urban planning field.

In the third stage, we mainly assessed the impact of urban facility elements on the perceived quality of urban streets, such as office facilities, dining facilities, medical facilities, etc. Firstly, the urban facilities data were cleaned and organized in order to screen the elements used as independent variables in this study. Then, the Pearson's correlation coefficient was used to analyze the correlation between the six perceptual dimensions and the various types of facility elements, exclude non-significantly correlated factors, and research the influence of the remaining ingredients through geographically weighted regression. Due to the apparent spatial heterogeneity of streets, we conducted a meso-scale study on the spatial quality of urban streets in typical regions. This explored the reasons for the formation of different street perception score differentiation by combining other regional characteristics and the influence coefficients of their influencing factors. We analyzed and summarized the degree of the various influencing factors and finally sorted out the influencing mechanisms behind them to provide a basis for the future improvement of street quality at the urban planning level.

In the fourth stage, we measured the influencing factors of urban street spatial quality at the micro level. In this part, we used semantic segmentation PSPNet to segment the street image, extracted the visual elements in the image, and calculated the green visual rate, sky visibility, interface enclosure, and other measurement indicators. The positive and negative impacts of the above indicators on urban street-space perception were analyzed through correlation analysis in order to guide future urban street-space transformation.

3.2. Study Area

Wuchang District is one of the administrative districts of Wuhan, located in the southeastern part of Wuhan. The district is located on the south bank of the Yangtze River, across the river from Hanyang and Hankou, adjacent to Qingshan District to the north of Yujiadou Luojia Harbor, and bordering Hongshan District to the southeast, with the Yangtze River in the west and the East Lake [50] in the east (Figure 1). In recent years, under the guidance of the Wuhan Municipal Government, Wuchang District has implemented a series of policies on the quality of urban streets, emphasizing the construction of a slow-pedestrian-friendly city and adapting to the transformation of urban streets from "car-first" into "people-first" [51]. As one of the nation's megacities, it is essential for Wuhan to realize high-quality development. Wuchang District has a long urban history, and its street spatial structure has specific historical characteristics. It has modern neighborhoods and historical street spaces under modern urban planning and diversity in street characteristics. Meanwhile, Wuchang District, as one of the central urban areas of Wuhan, has a high level of economic development. Therefore, Wuchang District has a high coverage of streetscape images, enabling the development of a more comprehensive and refined study of urban street space.

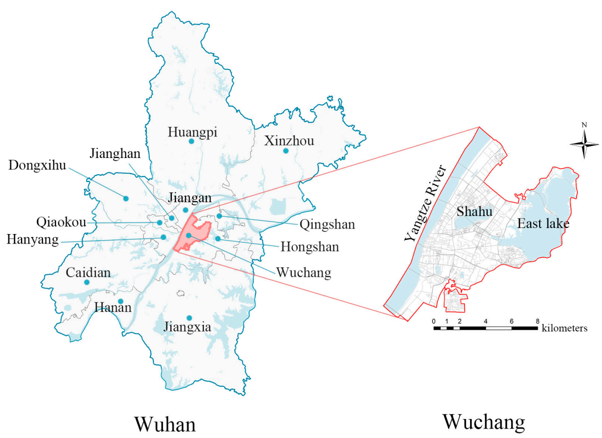


Figure 1. Schematic of the study area.

3.3. Acquisition of Research Data

(1) Wuchang District Street-View Image Data

Streetscape images can provide a wide range of geographic coverage and images, so streetscape image acquisition and extraction are critical channels for the large-scale measurement of urban spatial research. Streetscape images reflect the most direct visual scene of human vision and thus have a wide range of application value in urban street-space research. We acquired the streetscape images of Wuchang District through the API interface 'Baidu Map'. These streetscape images correlated with the road network and provided geographic coordinate information. Eventually, we collected more than 26,000 POI points, covering most of the Wuchang District area. River areas on the map do not have streets, and since there are several water areas in Wuchang District, they therefore do not have collection points. The location distribution of the street-view data collection points is not equidistant, meaning some areas are densely populated with collection points. Still, POI points provide more complete coverage of the overall land area. Street-view shooting is mainly performed using a street-view shooting vehicle shooting along the road. We collected four street-view images according to the four relative angles of each point. In order to obtain street-view pictures of the street-view points to the front, back, left, and right of the four directions of the sampling point, the azimuth angle was set to be from 0 degrees to 360 degrees, and a 360-degree panoramic street-view was formed in the end. The storage attributes of the street-view images include the X coordinate, Y coordinate, and azimuth angle. After cleaning the images, they were projected to the corresponding geographic locations.

(2) POI points for public facilities in Wuchang District

The POI points for public facilities in Wuchang District were obtained through the POI interface of the Baidu map and retrieved through administrative divisions. To facilitate the subsequent research, the POI data were defined to include detailed fields such as the POI name, latitude, longitude, and exact address. The categories included food and beverage facilities, governmental facilities, medical facilities, leisure and recreation facilities, etc.

3.4. Semantic Segmentation and Spatial Measurement Index Calculation of Street-View Images Based on Deep Learning

The machine learning algorithm represented by PSPNet was constructed based on a deep convolutional neural network that can process street scene images in depth [52] and recognize various elements in an image, such as the sky, sidewalks, cars, buildings, etc. PSPNet stands for a pyramid scene parsing network, a scene-analyzing network constructed using the pyramid pooling module [53]. Based on deep learning methods, it performs a pixel-level segmentation of the semantics of objects such as the sky, roads, and plants appearing in an image [54]. We chose this model because PSPNet produced a new mIoU accuracy record of 85.4% on PASCAL VOC 2012 and 80.2% on Cityscapes [55]. This model uses a technique that enables a more accurate segmentation of scene image elements. The street-view imagery from more than 26,000 collection points in Wuchan was segmented. In this study, the method is mainly used to obtain the percentage of each visual element of the street. A total of 14 visual elements are required to calculate the five spatial measurement indicators, and the 14-element segmentation results are shown in Table 1.

Combined with the segmentation results of street-view images, five spatial measures were selected in this study to quantify human visual elements. The application of green vision and sky visibility is very common in urban spatial measurements. Green space quality is often associated with urban health and has a certain impact on urban spatial perception [56]. Sky visibility is also important for the study of urban heat islands. At the same time, the sky represents infinity in space, which is also related to the visibility of the line of sight. It is one of the more important visual elements in human vision. Space enclosure degree is an important kind of public spatial measure. The degree of spatial closure has a significant influence on the perception of spatial preference attributes and the sensory feedback for mental health [57]. Therefore, it is indispensable to the measurement index of this study. The degree of motorization and non-motorization measures represent the urban population mobility and the urban traffic situation to some extent. In Chinese cities, the occurrence rate of non-motor vehicles is becoming higher and higher. They are not constrained by the motor vehicle lane, indicating that the impact this will have on pedestrian feelings is direct.

Table 1. Segmentation results of the 14 visual elements.

	Maximum	Minimum	Average	Standard Deviation
road	0.723	0.016	0.188	0.068
sidewalk	0.140	0.000	0.017	0.017
building	0.681	0.000	0.151	0.101
wall	0.172	0.000	0.005	0.009
fence	0.133	0.000	0.007	0.011
vegetation	0.713	0.000	0.205	0.154
sky	0.480	0.000	0.200	0.123
person	0.189	0.000	0.010	0.008
rider	0.025	0.000	0.001	0.001
car	0.983	0.000	0.191	0.064
truck	0.186	0.000	0.007	0.013
bus	0.115	0.000	0.001	0.005
motorcycle	0.048	0.000	0.002	0.004
bicycle	0.059	0.000	0.002	0.003

We calculated the spatial metrics from each visual element, and five metrics were selected for spatial metrics: the green vision index, sky visibility, degree of interface enclosure, degree of motorization, and degree of non-motorization.

(1) Green vision index

Green visibility can improve the attractiveness and visual experience of urban streets; the public's mental health is significantly affected by the perception of the amount of green in urban streets [58]. The green vision index refers to the proportion of green plants in the visual field, and the formula for its study is:

$$GVI_i = \frac{n_v}{n_i} \times 100\%$$

where GVI_i is the green vision index at the i-th position; n_v is the number of vegetation pixels of the street attraction; and n_i is the total number of pixels of the street-view image at the i-th location.

(2) Sky visibility index

The sky visibility index has a significant impact on metropolitan areas. It is an important factor in the urban heat island effect [59] that the area experiences, as well as a crucial factor in research into urban morphology. This indicator refers to the visual proportion of sky features in an image in this study, and its calculation formula is as follows:

$$SVI_i = \frac{n_s}{n_i} \times 100\%$$

where SVI_i is the sky visibility index at the i-th position; n_s is the number of sky pixels of the street's attractions; and n_i is the total number of pixels in the i-th location street-view image.

(3) Degree of enclosure

The degree of the interface enclosure of urban street space measures the enclosure of living street space by facilities such as buildings, walls, fences, etc., which in this study is the pixel occupancy of elements such as buildings, fences, walls, etc. in the image. The specific calculation formula is:

$$DOE_i = \frac{n_a + n_w + n_f}{n_i} \times 100\%$$

where DOE_i is the degree of enclosure at the *i*-th position; n_a is the number of architectural pixels of the street's attractions; n_w is the pixels of the number of walls of the street's attractions; n_f is the number of pixels of the fence of the street's attractions; and n_i is the total number of pixels in the *i*-th location street-view image.

(4) Degree of motorization

The degree of motorization impacts urban pedestrian mobility, which influences the environmental, socio-demographic, mobility, and road safety characteristics of pedestrian travel communities [60]. In this study, the degree of motorization is represented by the percentage of pixels in the image of the motorized elements framed in a given streetscape image. The formula is as follows:

$$DOM_i = \frac{n_b + n_c + n_t + n_m}{n_i} \times 100\%$$

where DOM_i is the degree of motorization at the *i*-th position; n_b is the number of bus pixels for the street attractions; n_c is the number of pixels for cars on the street's attractions; n_t is the number of pixels of the trucks at the street attraction; n_m is the number of motorcycle pixels in the street attraction; and n_i is the total number of pixels in the i-th location street-view image.

(5) Degree of non-motorization

The degree of non-motorization of urban streets reflects the traffic in the non-motorization driving space in the city, which is one of the indicators used to measure the chronic space in the city. This study mainly summed up the proportion of people, bicycles, and riders. The formula is as follows:

$$DON_i = \frac{n_p + n_e + n_r}{n_i} \times 100\%$$

where DON_i is the degree of non-motorization at the *i*-th location; n_p is the number of pixel points for pedestrians at that street point; n_e is the number of pixel points of a bicycle at that street spot; n_r is the number of pixel points of the rider at that street scene point; and n_i is the total number of pixels in the streetscape image at the *i*-th location.

3.5. Convolutional Neural Network-Based Scoring and Spatial Pattern Study for Scene Perception

This section quantifies the macro-level research into the perceived spatial quality of urban streets. The street spatial perception dataset is derived from MIT Lab's "Place Pulse2" project, an online data collection platform that collects people's perceptual evaluations of the appearance of cities. This dataset has massive data and wide coverage. However, there is still some specificity required for the accurate evaluation of the street perception score in China and its cities. Therefore, in this study, a pre-trained deep learning model with higher pertinence was selected to obtain the perception score of urban street-view images and carry out the analysis. The open-source model was developed and shared by China University of Geosciences (Wuhan). This is a deep-learning model with high precision and was pre-trained on a dataset of the Wuhan area [49]. After processing, the scores were finalized as shown in Table 2. The six street spatial perception scores are shown in Figure 2.

Table 2. The six perception scores for urban streets.

	Average	Maximum	Minimum	Standard Deviation
boring	57.81194	85.11137	23.5317	6.27788
beautiful	17.61704	54.10796	−22.4117	7.96088
depressing	56.69106	91.56737	34.66571	5.30669
lively	37.11306	86.62331	2.01155	9.80697
safe	37.37488	61.92188	15.30053	5.68273
wealthy	41.92913	79.03056	10.92321	7.75064

Figure 2. Map of the Wuchang District urban street perception score.

When conducting an in-depth study of the spatial pattern of urban streets, it is also necessary to judge the laws that exist in the spatial distribution. Therefore, we determined whether the space is dispersed or aggregated and studied the law of aggregation and the influence mechanism behind it. The analysis of the perceived spatial pattern of street spatial quality mainly needs to focus on the spatial distribution characteristics of the points and be combined with their interrelationships. Although the spatial relationship of the scores can be judged to a certain extent through the observation of the perception map, it is still necessary to further evaluate the spatial autocorrelation situation through calculation. The common basis for judging the spatial autocorrelation phenomenon is known as the spatial autocorrelation (Moran's I) index. Global Moran's I can statistically measure the relationship between the values of attributes of neighboring spatially distributed objects. The Moran's I calculation formula is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i - \overline{x})2} \tag{1}$$

where n is the total number of space units; x_i is the observed value at space location I; x_j is the observed value at space location j; W_{ij} is the weighting matrix for space; and $\overline{x}$ is the average value of all space units.

The Moran I index has a value range of [−1, 1], with a negative spatial correlation indicated if $I < 0$ and a positive spatial correlation if $I > 0$.

To further determine the type of numerical clustering in space, we used hotspot analysis to determine whether the space was positively or negatively correlated and to detect the location of clustered areas. Hotspot analysis is quantified by the Getis-Ord Gi* coefficient, which is calculated by the following formula:

$$G_i^* = \frac{\sum_{j=1}^{n} w_i x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{2}$$

where x_j is the attribute values of element i and element j; $w_{i,j}$ are the spatial weights of elements i and j; and n is the total number of elements in the dataset.

$$\overline{X} = \frac{\sum_{j=1}^{n}}{n} \tag{3}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2} \tag{4}$$

The z-scores and p-values obtained indicate where spatial clustering occurs for high- or low-value elements.

3.6. Study on the Correlation of Multi-Dimensional Elements of Spatial Quality of Urban Streets

This section studies the relationship between the spatial quality scores of urban streets and urban amenities. The primary method for quantifying and evaluating geospatial dimensions is geographically weighted analytical regression analysis (GWR), first proposed by Fotheringham, Brunsdon, and Charlton [61] in 1996. Geographically weighted regression differentiates the use of different operations at different scales, and each spatial location applies a unique algorithm for regression analysis. In this study, each of the six perceptual scores is used as a dependent variable, and facility points within the urban grid are operated as independent variables to explore the correlation between urban facility configurations and spatial quality scores and to identify the significant influencing factors.

Firstly, the range of Wuchang District was gridded with 100 × 100 m as the image element length and width, and the six perceptual scores were projected into each grid. For a single grid with multiple POI points, the average of the relevant attributes of all the points falling within the range was taken. After pre-processing the facility types, numerous types of facility points were obtained, such as those relating to government facilities, medical facilities, recreational facilities, parking facilities, transportation site facilities, tourist areas, cultural facilities, residential areas, public security and traffic police, large-scale shopping, and office buildings. After completing the above, the facility point POI data required processing. We projected it into the grid as a sum of quantities, i.e., we calculated the number of POI points in each image element. Regression analysis was performed using the perceived score as the dependent variable and the number of urban facilities as the independent variable. To better screen the independent variables, we used the Pearson correlation coefficient to determine whether the independent and dependent variables were significantly correlated. The independent variables that did not have a significant correlation were finally excluded. Additionally, because the total amount of data for some types of POI points was too small, they were also excluded. A geographically weighted regression was calculated for the final screening results. The formula is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i i = 1, 2, \ldots, n \quad (5)$$

where y_i is the value of the dependent variable at position i; $x_{ik}(k = 1, 2, \ldots, m)$ is the value of the independent variable at location i; (u_i, v_i) is the coordinates of sampling point i; $\beta_0(u_i, v_i)$ is the intercept term; and $\beta_k(u_i, v_i)$ is the regression coefficient of the kth independent variable x at sampling point i.

After the above work was completed, it was also necessary to correlate the urban microcosmic space measurement indexes. The quantitative calculation methods used in such exercises are Pearson coefficient correlation analysis and linear regression analysis, with the dependent variables being the six urban street perception scores and the independent variables being the five items of green visual index, sky visibility index, degree of enclosure, degree of motorization, and degree of non-motorization.

4. Results and Analysis

4.1. Analysis of Spatial Patterns of Perceived Spatial Quality in Urban Streets

The results of the global Moran's I calculations are shown in Table 3, where the Moran's I indices for all six perceptions are positive, indicating that the data exhibit a spatially positive correlation. The results of the spatial autocorrelation analysis for all six perceptions have high z scores and low p values, with small p values indicating that the observed spatial patterns are unlikely to arise from stochastic processes (small probability events). Therefore, hotspot analysis is also needed to detect agglomeration areas' locations. The hotspot analysis yielded six urban street perception clustering results (Figure 3). Figure 3a demonstrates the spatial clustering relationship between the high and low values of the boring score. According to the map, there is an apparent clustering of high values in the northeast region. This is the East Lake Tunnel section, which is perceptually exceptionally closed with only a monotonous view. Similar to this situation is the beautiful low-score aggregation of the East Lake Tunnel in Figure 3b. The five cross-river bridges over the east region also have low scores. Although the cross-river bridges have an open view range, the lack of landscape diversity may contribute to the high boring score. There is a wide range of low scores in the southeast area of Wuchang District, a university area with a long history of construction, rich cultural heritage, a beautiful green landscape, unique architectural and cultural attributes, and a beautiful campus environment. The low score aggregation of boredom here may be related to the diverse environment of the university campus. A similar aggregation of low scores is the depressing score in Figure 3c, both of which are negative evaluations; it can be assumed that the lower their perceived scores, the better the spatial quality. Figure 3b demonstrates the aggregation of high and low values of beautification. Wuchang District along the Yangtze River, which contains more Wuhan historical neighborhoods, cultural parks, and newly built residential areas, presents a more extensive range of score aggregation. It is one of the most critical sections of Wuhan's urban area style control. Figure 3c shows the depressing score aggregation. There is no wide range of high aggregations of depressing scores, but there are two low aggregations of scores near East Lake. Figure 3d shows the lively score; the overall dynamic low aggregation of scores in the area is more significant, and the high aggregation of scores in the area is not apparent and needs further study to transform it into a low aggregation of scores. In Figure 3e, in addition to the low-scoring aggregation near East Lake, there is also a low-scoring area in the eastern region, which has more old neighborhoods and older buildings. Hence, the site has a high population density but narrower roads, more on-street parking, and older facilities. The more aged settlement environment may create a sense of insecurity for pedestrians, resulting in lower scores. Another significantly low-scoring roadway includes the tunnel and viaduct, and the urban expressway harms pedestrians' perceptions of safety. The overall perception of affluence in Figure 3f is better, with high scores clustered mainly in dense urban residential and commercial areas and low scores primarily clustered around the East Lake neighborhood. The overall economic development of the Wuchang District is more advanced in the central metropolitan area of Wuhan. Generally speaking, the city's more prosperous commercial and residential areas have higher commercial value, and the affluence perception is consistent with the general perception.

Table 3. Statistics of the global Moran's *I* for the six perceptions of urban streets.

	Boring	Beautiful	Depressing	Lively	Safe	Wealthy
Moran's I	0.125	0.122	0.131	0.257	0.126	0.336
z-score	157.58	153.67	165.64	323.54	159.10	424.31
p-value	0.000	0.000	0.000	0.000	0.000	0.000

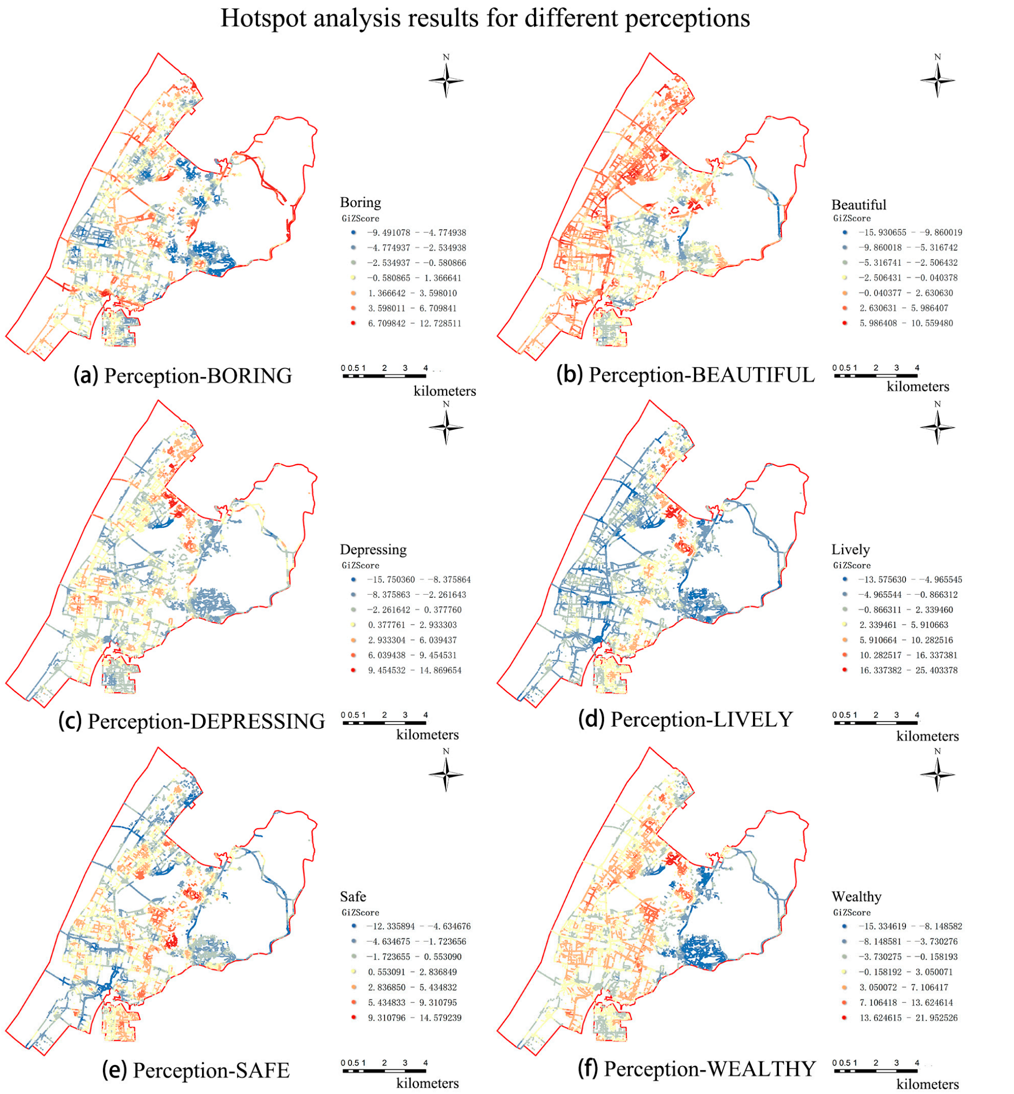


Figure 3. Cluster analysis of the high and low values of spatial perception of six streets.

4.2. Results and Analysis of Regression Analysis of the Spatial Quality of Urban Streets and Urban Amenity Points

Table 4 gives the local R2 of the six perception dimensions. The local R2 can be interpreted as the proportion of the variance of the dependent variable covered by the regression model globally. As can be seen in Table 4, the local R2 for all six dimensions is above and below 0.4; due to the complexity of the influencing elements of urban spatial perception, a fit of 0.4 can be judged as an acceptable range. Since urban street space is closely related to geographic location and its perception scores are spatially heterogeneous, it is also necessary to pay attention to the variability in the local R2 and the fluctuation of the correlation coefficient. Figure 3 shows the values of localized R2, which we segmented. Regression model instability occurred in some places as a result of the absence of street attractions and the scarcity of dependent variable data. However, because they are uncommon, these locations were left out of the study. When the fit is too small, the regression coefficients cannot sufficiently explain the relationship between the independent and dependent variables. As shown in Figure 4, the fit is less than 0.2 (blue area). As such, subsequent studies should carefully refer to the model interpretation. Still, the proportion of this part is small so that the regression coefficients can be used in assessing most dimensions of the relationship between the spatial quality of the city street and the urban amenity points. Different influences have different interpretations in other locations. As such, we organized and analyzed each influential element for the six different perception types. The correlation coefficient represented the effect of different facility point elements. There were nine types of facility point elements used as independent variables in this study: restaurants, office buildings, residential locations, cultural facilities, transportation sites, parking lots, recreational facilities, medical facilities, and government facilities.

Table 4. Table of the R2 results of the six categories of the perceptual regression models.

	Boring	**Beautiful**	**Depressing**	**Lively**	**Safe**	**Wealthy**
Local R2	0.398	0.388	0.414	0.413	0.419	0.422

A negative influence coefficient means the dependent variable contributes negatively to the perceived score. In contrast, a positive influence coefficient implies that the dependent variable contributes positively to the perceived score. The absolute value of the influence coefficient means that a dependent variable in this position contributes more to the perception score. The nine urban amenity elements contain two types of influence. The first category includes the global, entirely positive influence elements, i.e., they are positively influenced globally. The second category addresses local differential influence factors, which refer to factors that are positively influenced in local areas and negatively influenced in regional areas. Let us take the boring perception as an illustration. Figure 5 shows the localization of the influence coefficients of urban facility elements on the boring perception. According to their coefficients' positive and negative values, we classify the results as follows: parking facilities and medical facilities are entirely positive elements, and food and beverage facilities, office buildings, entertainment and recreational facilities, and government facilities are positive elements with local differences. The results of the other five perceptual scores are categorized along the same lines, and the results are shown in Table 5. These will serve as a reference for the later portion of the local impact study. The values of the coefficients can also reflect the local impact on the score situation. For areas where a facility point has a positive effect, adding a particular type of facility point at a location with a higher impact coefficient can have a more significant effect when it is necessary to improve a specific perceptual score. For areas where a facility has a negative impact, a positive perception can be enhanced by reducing the number of amenity sites, and a negative perception can be reduced by increasing the number of facilities in a particular location.

The six perceptions were divided into positive and negative perceptions, with the positive ones including beautiful, lively, safe, and wealthy, and the negative perceptions being boring and depressing. The optimization goal of urban street-space perception is to enhance positive perception and weaken negative perception. Therefore, in urban planning practice, we need to focus on the low-value aggregation of positive perceptions and the high-value aggregation of negative perceptions, corresponding to the low-value or high-value aggregation in Part 4.1; the typical area schematic is shown in Figure 6. Since some of the areas with low-value or high-value clusters do not have the conditions for adjusting the facility points, such places were not included in the discussion of optimizing the spatial perception of urban streets through the facility points, such as the cross-river bridges, tunnels, and the interior of university campuses, and therefore are excluded from the discussion of the typical street spaces in this section.

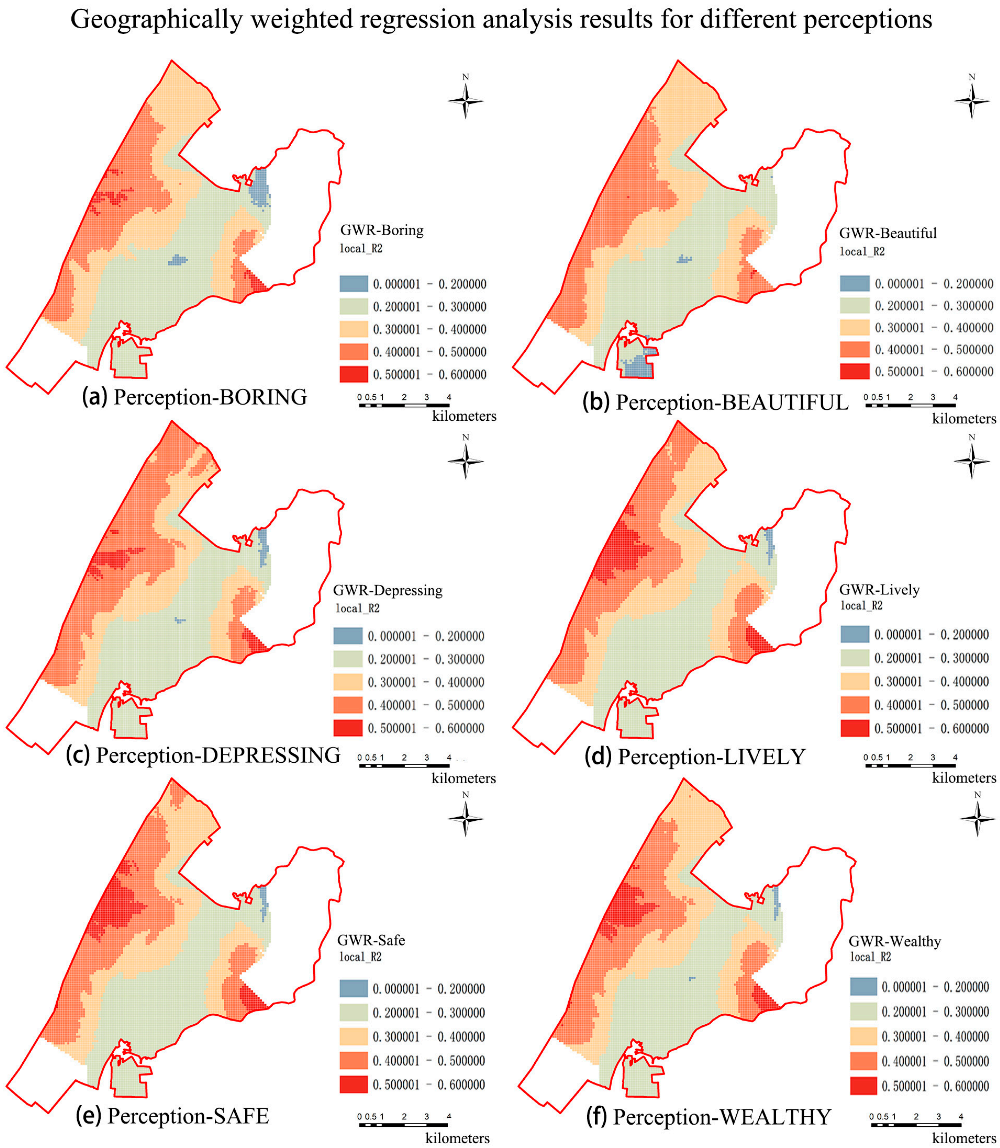


Figure 4. Local R2 scores.

To better screen the typical regional influencing factors and analyze them, we categorized the critical influencing factors of the selected typical area. The categorization standard is that if the proportion of the region with an influence coefficient greater than five is greater than 60%, it is recognized as a key influencing factor. The results are shown in Table 6. The selected key influencing factors can provide a reference for the planning of urban facilities in the Wuchang District. Among them, the statistics found that the influence coefficient of each type of facility land has a certain influence on beauty, but the categories and their regions with contribution values greater than five account for less. Therefore, further urban micro-influence factors must be implemented in a supplementary fashion.

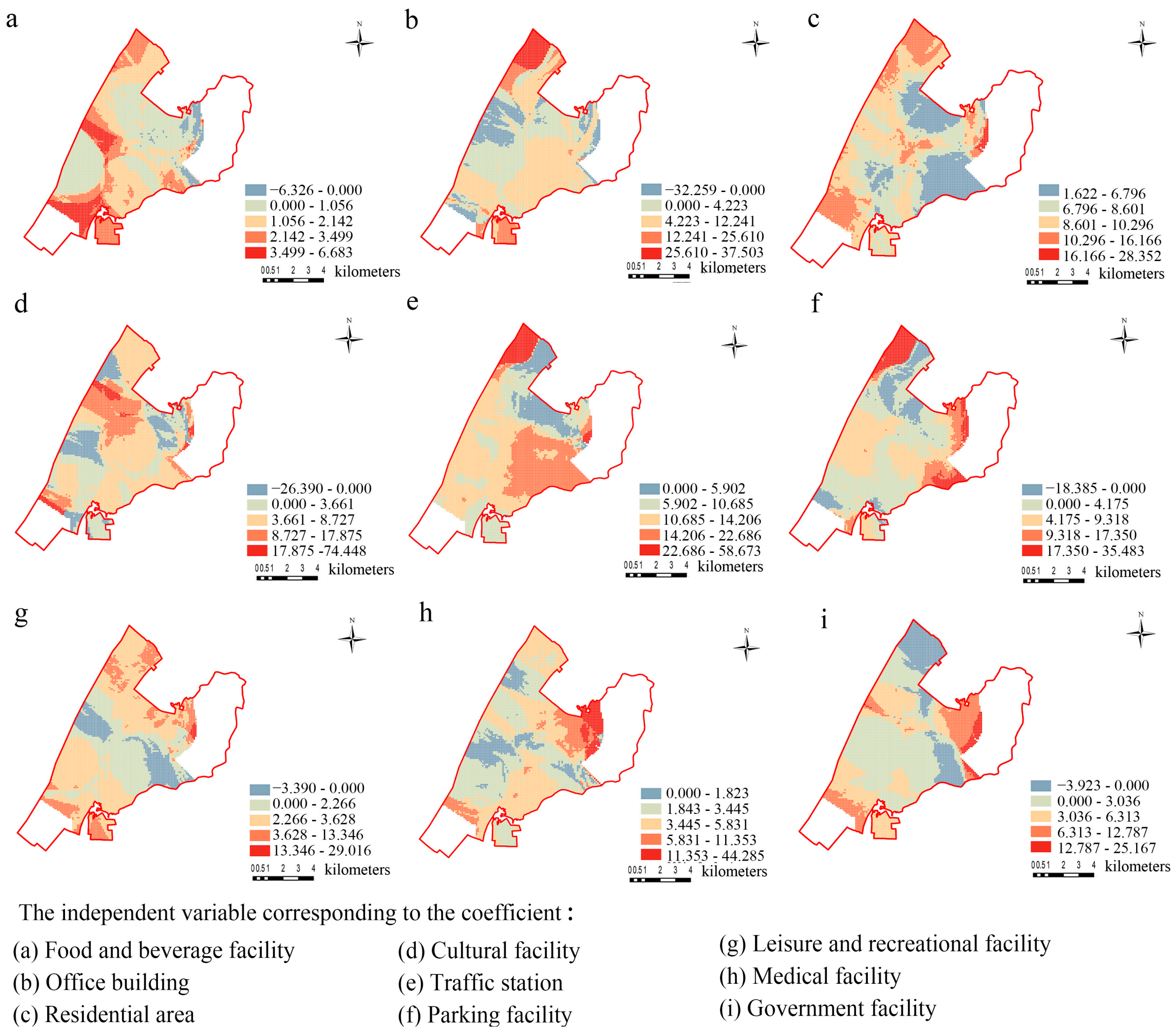
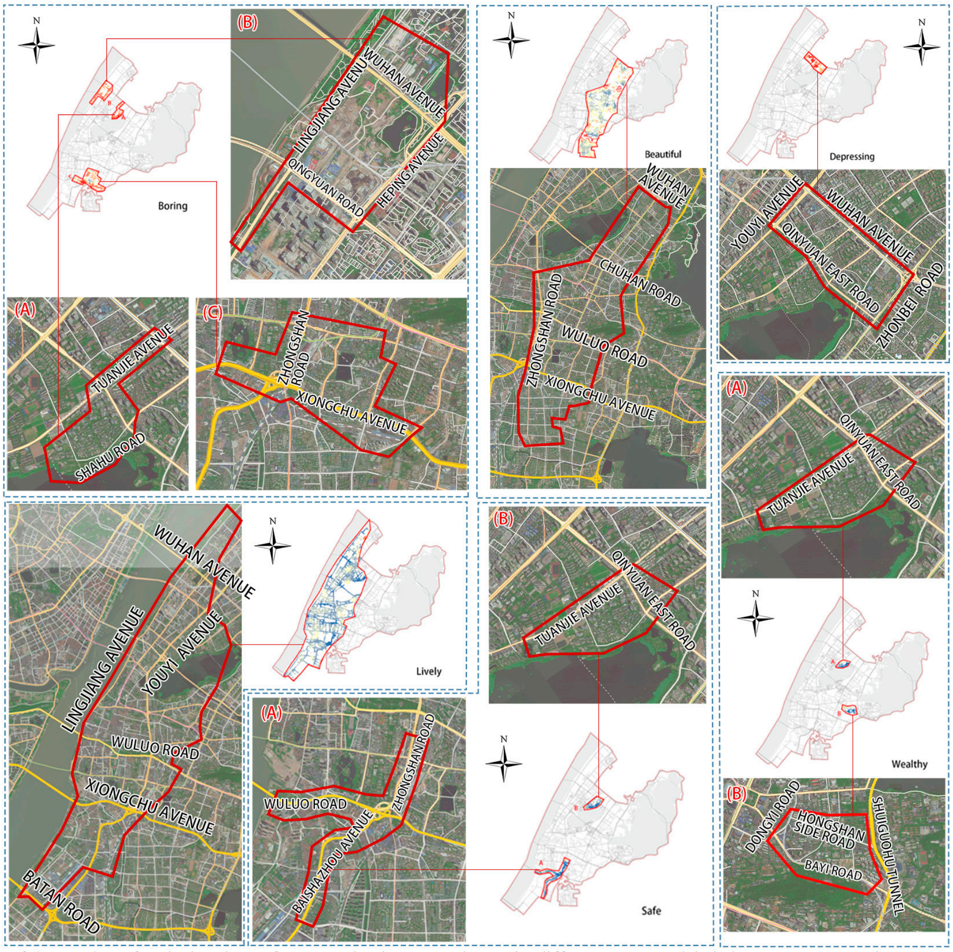


Figure 5. Coefficients of influence of urban facility elements on the boring perception.

Table 5. Classification of impact types.

	Boring	Beautiful	Depressing	Lively	Safe	Wealthy
Full positive influence	Residential area; traffic station; parking facility; and medical facility	Food and beverage facility; residential area; traffic station; recreation and leisure facility; and medical facility	Parking facility; medical facility; and government facility	Food and beverage facility; residential area; traffic station; medical facility government facility; recreational facility; and parking facility	Government facility; medical facility; recreation and leisure facility; cultural facility; and wealthy facility	Recreation and leisure facility; traffic station; and government facility
Impact of localized influences	Food and beverage facility; office buildings; cultural facility; recreation and leisure facility; and government facility	Office building; cultural facility; parking facility; and government facility	Food and beverage facility; office building; residential area; cultural facility; traffic station; and recreation and leisure facility	Office building; cultural facility; and recreation and leisure facility	Food and beverage facility; office building; parking facility; residential area; and traffic station	Food and beverage facility; office building; cultural facility; traffic station; parking facility; and medical facility



If the number of typical regions of a perception is greater than 1, its different areas are labeled (A) or (B) or (C) in turn. The letters of the regions correspond to the descriptions in Table 6.

Figure 6. Schematic diagram of a cluster area with typical high or low scores.

Table 6. Typical regions and their key influencing factors.

	Boring	Beautiful	Depressing	Lively	Safe	Wealthy
Regional situation	(A) Sand Lake Road and its vicinity (b) East of Linjiang Avenue, west of Heping Avenue (c) Around and north of Xiongchu Avenue	South-central area of Wuchang District	South of Xu Dong Avenue. North of Qin Yuan Zhong Road	Roads along the Yangtze River and surrounding residential areas	(A) Zhongshan Road Tunnel Section, Po On Street, and Baishazhou Elevated Road and its surrounding side roads (B) Sand Lake and its surrounding roads	(A) Sand Lake Road and its surrounding roads (B) Chagang Community and vicinity
Key impact elements	(A) Cultural facilities (negative correlation); medical facilities (B) Office building; residential area; cultural facility; and traffic station (C) Office building; residential area; and traffic area	Office building	Residential area, parking facility (negative correlation), and medical facility	Residential area and traffic station	(A) Residential area and traffic station (B) Cultural facilities	(A) Cultural facility (B) Office building and parking facility

Negative influencing factors are marked in parentheses and positive influencing factors are unmarked.

4.3. Analysis of the Impact of Spatial Visual Elements on the Spatial Quality of Urban Streets

We calculated the values of the five spatial metrics for each streetscape collection point using the formula shown in Part 3.4. Then, we tested the correlation between the six perception scores and the five primary spatial metrics. The results showed that all the factors were significantly correlated, meaning that linear regression analyses could continue. The regression analysis results are shown in Figure 7, where the lines of different colors represent the influence coefficients of the five spatial measures under the spatial perception of different streets. The longer the lines of color in the bar graph, the higher the absolute value of the standardized beta coefficient. Firstly, the respective factors under the six perceptions were compared and analyzed. Under the boring perception category, all five spatial metrics had a negative impact on the boredom score. Still, the degree of influence varied, with the green visual index having a significantly higher negative impact than the other categories, followed by the degree of enclosure and the sky visibility index. The degree of non-motorization had a more negligible, albeit still negative, impact. In the beautiful perception study, the green visual index and the sky visibility index had the most significant positive effects. Sky and plant visibility were essential for building a beautiful ecological and visual environment that is conducive to enhancing the spatial experience of pedestrians. Thus, these two factors were more critical for pedestrians' perceptions of space. The degree of non-motorization had a negative influence, and it can be presumed that people's perception of the beautification of the street space was hindered by people or bicycles. For the depressing perception, the higher the degree of enclosure and motorization, the more depressing the urban street space. However, sky and green visibility had a significant adverse effect on the perception of pedestrian depressiveness, necessitating a focus on these elements in the discussion of the design methods used to reduce the depressiveness of urban street space. All five spatial measures positively impact the lively feeling of street space. Still, the degree of enclosure, sky visibility index, and green visual index have a significantly higher impact than the other two indicators. The degree of enclosure is often closely related to the height and density of the surrounding buildings, which indicates that the closer the area with a high perception of urban liveliness value is, the higher the density and height of buildings tend to be. The perception of a lively core correlates with an area's prosperity. The degree of enclosure, green visual index, and sky visibility index significantly positively affect the perception of safety. However, due to the negative impact of motorization on safety perception, one way to improve security is to reduce the occurrence rate of motor vehicles. Under the influence of affluence, the degree of enclosure and sky visibility index have a more crucial impact, and the degree of non-motorization plays a negative role. Overall, the green visual index, sky visibility index, and degree of enclosure greatly influence each aspect of perception, providing clear guidance for the research strategy of quality improvement in terms of the spatial dimension of urban streets.

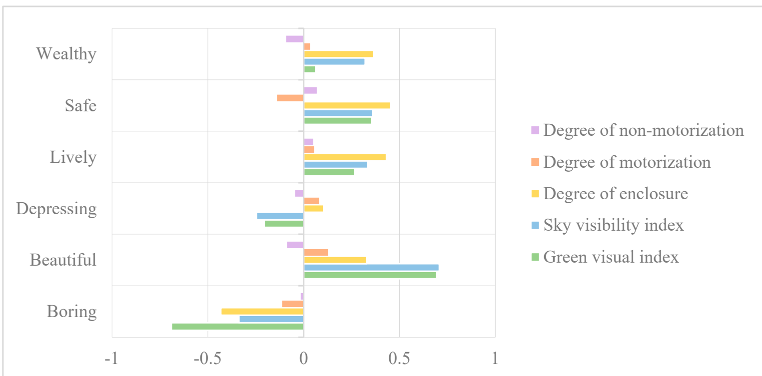


Figure 7. Histogram of the beta coefficient of the regression analysis.

5. Discussion

Influence studies on the spatial quality perception of urban streets play complementary roles across different analytic dimensions. This study constructed a quantitative research framework to investigate the spatial quality perception of urban streets on macro-, meso-, and micro-multi-dimensions. This study formed an urban perception map of the Wuchang District in Wuhan, China, and carried out a spatial pattern analysis at the macro level. At the meso level, the correlation between street perception and critical urban facilities in typical areas was studied to provide a reference for future urban facility planning. At the micro level, this study investigated the influencing factors of street space based on the scale of human perspectives, which provides a reference for the design update of specific spaces. The conclusions of the leading research elements of this study are discussed below.

5.1. The Aggregation Characteristics of the Urban Street Spatial Perception Score in Spatial Pattern

The results supported the existence of significant spatial agglomerations in all six categories of urban street perception, but these agglomerations were considerably different from one another. The high-score aggregation of the beauty perception and the low-score aggregation area of the lively perception were present among them in a significant area, and the spatial characteristics demonstrated the continuity of the block. These regions border the Yangtze River. The cluster scores of the four perceptions of boredom, depression, safety, and wealth that were high or low tended to be localized. This phenomenon may be determined by the peculiarities of the campus street. On the campus, there are significant differences from cities in terms of vehicle density, population density, building density, etc. within the field of view. The spatial perception of streets in nearby cities outside of school differed significantly from the scoring results for the streets on campus when the campus streets were evaluated using the perceptual scoring criteria of regular city streets. In terms of specific perception, we also found the following characteristics:

First of all, there is a correlation between a city's beauty and its prosperity. The more a city is developed and includes environmental regulation, the more beautiful it is considered to be in contrast to areas in its proximity. Second, the perceptions of beauty and liveliness in the areas along the river are scored a different way, with the scores in the vicinity of the city's developed sections being lower. Older commercial housing communities and numerous historic structures can be found nearby. This serves to remind urban planners that there are measures they can take to improve the vibrancy of urban centers. In addition, urban tunnels and bridges across the river are significant agglomeration areas with high scores of urban negative perceptions, and they are also low-value aggregation areas of urban safety perception. It is important to further investigate this finding in conjunction with the unique street situation since high or low levels of boredom are primarily found in specific neighborhoods and are related to the spatial characteristics of a small number of streets. In the study of spatial patterns, the perception of urban affluence basically corresponds to the level of regional development.

5.2. Discussion on the Difference of Factors Affecting the Perception of Street-Space Quality at the Level of Urban Facilities

The aforementioned research has already demonstrated that urban facilities exert a certain level of influence on the perception of urban street space, but the contribution to the scores varied among facilities with different functions. At the same time, the degree of influence that a single type of urban facility has on a certain street-space perception also differed by location. Therefore, characteristic analyses need to be conducted based on typical regions. The focus of this study is on areas with low scores that are actively perceived and areas with high scores that are negatively perceived. The results showed that among the low-scoring factors of boredom perception, cultural facilities, medical facilities, office buildings, and residential areas were more crucial. The effects of cultural facilities in different regions may be positive or negative. Urban cultural facilities contain different specific attributes, such as university facilities, libraries, theaters, etc., and different categories have different effects on the perception of boredom. This might be connected to more detailed types of cultural facilities, according to speculation. Office buildings, residential areas, and traffic stations all contributed greatly to the boredom perception score. In terms of POI location, the contribution of urban facilities to the beauty perception score was relatively low, except for office buildings, so the explanation of influencing factors at the micro level is more important. Residents and medical facilities were the key influencing factors in depressive perception. Going to the hospital is a symbol of illness, and the hospital may bring negative psychological feelings, thus contributing more to the depression score in that geographical location. In a Chinese context, the general downtown area symbolizes bustle and better security. Office buildings, parking lots, and cultural facilities are higher in more affluent areas, meaning that identifying similar facilities in the field of view can lead to an awareness of the affluence of the area.

The study's results on the impact of urban facilities on urban street space reveal the relative importance of the relevant factors in the perception of urban quality. It was found that the impact of facilities on spatial perception was characterized by significant geographic variability, which received less attention in many previous studies. We also screened the findings for the critical factors of urban facilities in high- or low-value areas, constituting a new research framework under the perspective of spatial differentiation. On the other hand, this part of the study can also assist practitioners in finding the pivotal factors of poor quality. Urban planning practitioners can supplement, reduce, or transform urban facilities with these pivotal factors to establish a better basis for planning and design.

5.3. Discussion of the Differences of Factors Influencing the Spatial Quality of Urban Streets at the Urban Micro Scale

Studying the influencing factors at the microscale can help urban renewal designers better understand the elemental role of mechanisms at the human-view scale. Due to the limited interpretation degree of facility planning, although the influence of facility functions can be mined to a certain extent, the visual indicators at the micro level can be an important part of the spatial design. First, we found a significant correlation between the five indicators selected for the study and the six perceptions. However, the positive, negative, and contribution of different indicators varied, so specific analysis was necessary. The results showed that the green vision index and sky visibility degree had a significant effect on reducing negative perception (boring, depressing perception) and increasing positive perception (beautiful, lively, safe, and wealthy perception). Among them, the positive influence on the perception of beauty and the negative impact on the perception of boredom were the most prominent. Areas with high levels of affluence tend to have cleaner urban greenery. Some scholars have pointed out that healthy and tidy trees contribute to the beauty and active perception of cities [56]. Thus, this conclusion is consistent with the general consensus and earlier research. Urban customers are ostensibly willing to pay more for residences that showcase the surrounding environment's natural components (sky and vegetation) [62]. This explains why increased sky visibility and green views resulted in increased wealth perception. The five perceptions of wealth, safety, liveliness, depression, and beauty were all positively influenced by spatial enclosure; however, the perception of boredom was negatively impacted. In addition to focusing on the green vision index and sky visibility degree, the influence coefficient of the degree of motorization and non-motorization could be considered an auxiliary consideration due to its comparatively low absolute value.

Designers can improve the quality of the street by enhancing the urban ecological landscape. For areas with better environmental terrain, the spatial quality of streets can be improved by adjusting the degree of spatial enclosure. Since the positive and negative effects of a certain index on different perceptions vary, the specific spatial improvement should be designed to take into account the specific conditions of reality. For example, the degree of enclosure is a positive factor in positive perception, but it is also positive for the sense of depression, meaning that comprehensive consideration is desirable. In terms of traffic, it is worth noting that the emergence of motor vehicles was negative for safety perception, but that non-motorized vehicles were positive. Positive perceptions can be achieved through the study of the degree of influence. For example, neighborhoods with high safety scores should adopt pedestrian–vehicle segregation to weaken the impact of motor vehicles on the street, enhance the optimization of the pedestrian experience, and achieve a human-centered area. This section of the study adds further information to the facility planning and spatial pattern of perception scores.

6. Conclusions

This study constructs a research framework for urban street quality perception and its multi-dimensional impact based on multi-source data, utilizing urban big data, semantic segmentation, regression modeling, and other quantitative technical tools. Unlike traditional single-dimension measurement and analysis, this study constructs a quantitative framework for urban macro-level, meso-level, and micro-level multi-dimensional integrations. Among them, the gathering area of beauty and liveliness perception showed regional continuity along the river, while the aggregation of boredom, depression, safety, and wealth perception scores was more scattered.

Through hotspot analysis, we identified typical areas in the study area and uncovered the typical influencing factors. For typical regions, the low-score aggregation area of positive perception and the high-score aggregation area of negative perception are worth noting. Therefore, we conducted an analysis of the magnitude of the influence of typical influencing factors. This can provide some guidance for urban facility planning; however, the impact study of urban facility dimensions is limited. Following this, we explored the differentiated impacts of urban street-space quality at a micro-urban scale. The positivity or negativity and the contribution of different spatial measurement indicators varied. Greenery, sky, and the degree of spatial enclosure contributed more to the perception of urban streets than motorized and non-motorized vehicles did. The detailed analysis results provide guidance for micro-space design strategies in urban renewal.

We confirmed the spatial pattern of the high and low aggregation of quality perception in the studied urban areas and summarized the influencing mechanisms, showing that the urban facility layout and human-visual elements complement each other. We then explored the ways in which it is possible to enhance urban space, finally forming a complete research system. The ideas and methods adopted in this study can effectively realize the measurement of urban streets' spatial quality and guide urban renewal measures. The research results provide methodological value and a technical reference for future urban development.

Facing the challenge of the high-quality development of cities in the context of urbanization, focusing on street space and the study of urban street spatial perception is of great significance in shaping high-quality space and realizing high-quality development. This study recognizes the spatial pattern and multi-dimensional influence of urban street-space quality perception in the Wuchang District in Wuhan, China, as an example. However, this study still has the following limitations: The first is the data source limitation; although the technology behind street image maps is mature, some of the collection points at the edge location were not dense enough, and there was a local region of collection points insufficient for data calculation. Additionally, due to seasonal variations, weather patterns, and limitations of acquisition time, street-view images may have partially affected the accuracy of the findings. Secondly, due to the complexity of the influencing factors of urban quality perception, some influencing factors were still not involved. In future studies, it is crucial to expand on more comprehensive and advanced techniques for big data collection. The availability of wider and more precise street-view data is critically important for research into the perception of urban street spaces. In the future, we will further explore more influencing factors of urban spatial quality (e.g., the spatial history dimension, socio-economic dimension, urban management dimension, etc.) to assess the influence of different factors on the perception of urban street quality. We will continue to deepen our research in the direction of broader types, larger areas, and more detailed techniques.

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